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A stochastic multi-objective optimization model for renewable energy structure adjustment management – A case study for the city of Dalian, China

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ABSTRACT

Due to the depletion of traditional resources and the deterioration of environmental quality, Dalian has always encouraged the explorations and utilizations of renewable energy sources. The research objective of this study is to develop a multi-objective stochastic chance constrained programming (MOSCCP) model for assisting local government to design and execute rational energy exploration and management strategies. The main advantage of this model is that it effectively broadens the decision maker's choice space and provides a more balanced optimization plan. A variety of renewable energy exploration schemes were identified under the reciprocal influence of different weight combinations and constraints-satisfaction levels. The calculation of power generation considering the variation in the meteorological factors was incorporated into the proposed optimization model, which effectively avoid the potential imbalance between electricity supply and demand under climate change. The obtained results verified that the abundant renewable energy sources in Dalian play an important complementary role to traditional energy, where the wind and solar energy always occupy a dominant position in the renewable energy utilization process with an optimal mix of around 83.6% of wind, 10.5% of solar, 5.8% of hydropower and 0.1% of biomass energy generation. In addition, the climate change scenario certainly altered the electricity demand and provision magnitudes, but did not markedly change the core role of wind and solar energy.

1. Introduction

With rapid socio-economic development, the energy demand of most cities in China has increased significantly. In order to effectively mitigate the shortage crisis of traditional energy resources (i.e. coal and fossil fuel) and then reduce the pollutants load during their utilizations, at this stage, the utilization of conventional energy sources was restricted, while the proportion of clean or renewable energy exploration was increased dramatically (Creutzig et al., 2017). For example, the city Dalian is an important economic, trading and port city on the eastern coast of China. At present, the energy structure in Dalian is still dominated by traditional fossil fuels, such as petroleum and coal. According to incomplete statistical results, in 2016, the fossil energy consumption of industrial enterprises reached 69.24 million tons of standard coal, which was more than 90% of total energy consumption. In detail, the coal consumption was 24.53 million tons of standard coal, accounted for 35.4% of total energy consumption; the oil consumption was 42.34 million tons of standard coal, accounted for 61.2%; the gas consumption was 2.37 million tons of standard coal, accounted for 3.4%. In fact, as above mentioned, the excessive exploration and utilization of traditional energy forms might lead to critical energy crisis and pollution issue. Therefore, how to realize efficient energy structure adjustment for mitigating even eliminating these issues and was necessary (Fang et al., 2017).

Previously, the municipal government agencies and scientific research institutes in Dalian have proposed a series of positive measures, including the establishment of the ecological civilization system, the industrial structure adjustment and improvement, as well as the regional spatial location optimization. For instance, in April 2017, the province Liaoning has launched the document “The Guidance of the People’s Government of Liaoning Province on Optimal Adjustment of Industrial Layout and Structure”. In July of the same year, the Dalian Municipal Government has issued the document named as “The Structural Change in the Supply Side of Resources and Environment”.

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Although the energy shortage and environmental pollution were partly solved through a series of measures; however, the failures to establish rational energy structure and realize the coordinate development among the economy, resources and environment still exist. This is because: (i) Due to the lack of some necessary quantitative analysis and assessment approaches, existing energy planning and management patterns were designed based on subjective experience and incapable of providing accurate and reasonable choices to the local managers; (ii) Energy management system is a comprehensive and complex system with multiple system factors and intricate interaction relationship. It is challenging to design and implement reasonable energy structure adjustment and development patterns. (iii) Major parameters of the energy structure adjustment optimization model exhibited obvious uncertain characteristics. This would bring the difficulties in the model formulation and result generation. For example, available energy supply was affected by meteorological factors, such as wind speed, radiation and rainfall; similarly, the energy demand is affected by many factors including the temperature, population and gross domestic product (GDP). Therefore, it is essential to formulate a reasonable energy structure adjustment optimization model that based on current energy supply and demand situation, environmental quality, as well as energy structure analysis, with the capabilities of tackling various uncertainties through a series of simplifications and assumptions.

In the last few decades, a variety of uncertain optimization methods such as stochastic mathematical programming (SMP), fuzzy mathematical programming (FMP) and interval mathematical programming (IMP) and their combinations have been developed and applied in many fields (Feng et al., 2017; Raskin and Sira, 2016; Xu et al., 2016, 2017a,b; Zare et al., 2018; Zhang et al., 2018). The previous applied results showed that existing uncertain optimization methods are not only suitable for solving practical environmental system planning and management problems, it also has the ability to tackle the optimization problems related to energy management such as energy distribution, management and structural optimization (Han et al., 2008; Ji et al., 2015; Liu et al., 2017; Marino et al., 2018; Shah et al., 2018; Xu et al., 2009; Zhang et al., 2017; Zhou et al., 2015). For example, Shah et al. (2018) developed a stochastic chance-constrained optimization model for assisting local governments to regulate the mix of recyclables embedded in every dustbin. Zhang et al. (2017) proposed an inexact multistage stochastic chance constrained programming model, which could provide optimal water allocation schemes for multiple users during multiple stages. Marino et al. (2018) formulated a stochastic two-stage chance-constrained programming model for realizing reliable microgrid operations under demand uncertainty. The obtained results demonstrated the advantages of proposed model in the economic aspect. As shown in applied results, SMP model could effectively deal with the energy management issue and then help decision makers to design and execute optimal strategies under different economic, environmental and risk restrictions. Nevertheless, most of the studies were mainly concerned for traditional energy planning and management, where the renewable energy was seldom involved for. Moreover, most of the optimization models were aimed at minimizing the economic cost or maximizing the system benefits, while other important objectives such as the minimization of the pollutants emissions, the stability of power generation technologies and equilibrium development of various energy sources forms, are considered rarely. In addition, the previous studies often neglected the influences of the meteorological factors on energy supply and demand amounts. Compared with other SMP models, the stochastic chance-constrained programming (SCCP) was extensively used due to its less computational burden and relax constraints limitations (Ding et al., 2017; Han et al., 2018; Xie et al., 2017a,b). In order to ensure that designed energy structure was capable of realizing the targets for the economic optimality, environmental friendliness and technical feasibility under the complexities and uncertainties, in this paper, a climate change scenario analysis based MOSCCP model was formulated for generating optimal electricity provision alternatives sourced from the renewable energy forms in Dalian.

Specifically, this paper will (i) formulate and solve the MOSCCP model in the Section 2; (ii) introduce the parameters information and existing problems associated with the renewable energy planning, management system of Dalian in the Section 3; (iii) exhibit and analyze the variation trends and characteristics of generated energy structure adjustment schemes in the Section 4; moreover, the influences exerted by the climate change on the energy structure adjustment and provision patterns and the discussions in the advantages and drawbacks of formulated optimization model also were included in this section; (iv) the conclusion is drawn in the Section 5.

2. Formulation and solution of the renewable energy structure adjustment optimization model of the city Dalian

Local managers whose mainly responsibility is it to design and implement the optimal energy structure adjustment and electricity provision schemes, which are capable of realizing the cost minimization (or benefit maximization) and improving the energy exploitation and utilization efficiency (Pereira et al., 2016). However, the energy planning and management system is usually complex and comprehensive, involving multiple processes (including energy exploitation, transportation, transformation and supply) and components (i.e. energy demand, various available energy forms and the pollutants generated by the energy utilizations). It will lead to the great disturbance in designing and generating rational management patterns. In addition, the investigated and analytical results of studied region shows that there is often a wide range of the uncertainties and complexities are associated with the system components and their interactive relationships (Xie et al., 2017a,b). Most important of all, it is difficult to reflect the system objective by one indicator, but it is often incongruous or even contradiction when take multiple indicators into account (Li and Qiu, 2016). Multi-objective programming (MOP) model is capable of selecting the most appropriate scheme under multiple conflict planning objectives (Charnes et al., 1989; Fan et al., 2010). Therefore, under the context that Dalian is rich in renewable energy and municipal government provides the policy support, to effectively handle the problems mentioned above, a multi-objective stochastic chance-constrained programming model is formulated, in which two periods (i.e. 2010 and 2020) are considered as the base and target year, respectively. The optimization model is written as follows:

Objective functions:

$$\text{Maximize } f(x) = \sum_{i=1}^{n} x_i g_i \tag{1a}$$

$$\text{Minimize } g(x) = \sum_{i=1}^{n} x_i c_i \tag{1b}$$

$$\text{Maximize } h(x) = \sum_{i=1}^{n} \phi_i x_i / e_i \tag{1c}$$

$$\phi_i = 1 - x_i / \sum_{i=1}^{n} x_i \tag{1d}$$

where i is type of energy sources ($i = 1$ for wind energy, $i = 2$ for tidal energy, $i = 3$ for solar energy, $i = 4$ for biomass energy, $i = 5$ for tidal flow energy); x_i is the annual exploration amounts of various renewable energy forms, which is defined as the decision variable, (million kWh); Eq. (1a) is the revenue function, which reflects the economic performance of the entire system, (10^4 RMB); Eq. (1b) is the objective value representing the carbon dioxide (i.e. CO_2) emission volumes during the energy exploitation and utilization, (ton); Eq. (1c) is the exploration ratio which indicates the utilization level of various energy forms; g_i, c_i, e_i are the unit revenue, (RMB/kWh), carbon dioxide emission volume

(g/kWh) and exploited energy volume, (million kWh), respectively; ϕ_i involved in Eq. (1d) is the function for calculating the weight coefficient of the exploration proportion. Above all coefficients are designed as the fixed values.

Subject to:

(1) Constraints for energy supply and demand balance:

$$x_i' \le x_i \le X_i \tag{1e}$$

$$X_{e\min}(s) \le \sum_{i=1}^{n} x_i \le X_{e\max}(s) \tag{1f}$$

$$\sum_{i=1}^{n}\left(x_i t_i / \sum_{i=1}^{n} x_i\right) \ge \omega_t \sum_{i=1}^{n}\left(x_i' t_i / \sum_{i=1}^{n} x_i'\right) \tag{1g}$$

where x_i' represents the explored amount in 2010, (million kWh); X_i is the allowable maximum exploitable amount in the future, (million kWh); X_e is the annual energy demand, (million kWh); $X_{emin}(s)$ is regulated minimum energy demand, which is assumed as the random variable following the normal distribution, (million kWh); $X_{emax}(s)$ is designed maximum energy demand, which also is the random variable following the normal distribution, (million kWh); t_i is annual operational hours for various energy sources, (h); ω_t represents the coefficient for reflecting the operational time. Constraint (1e) indicated that the exploration amounts of candidate energy forms in the planning year should be less than or equal to the maximum available amounts; meanwhile, it should be greater than or equal to the exploration amounts in the base year. Constraint (1f) regulated total energy output in the planning year should be limited in predetermined range composed by the minimum and maximum energy demand. Constraint (1g) required that the running time in planning year should be more than that in base year.

(2) Technical constraints:

$$\sum_{i=1}^{n}\left(x_i \alpha_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\alpha \sum_{i=1}^{n}\left(x_i' \alpha_i' / \sum_{i=1}^{n} x_i'\right) \tag{1h}$$

$$\sum_{i=1}^{n}\left(x_i \delta_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\delta \sum_{i=1}^{n}\left(x_i' \delta_i' / \sum_{i=1}^{n} x_i'\right) \tag{1i}$$

$$\sum_{i=1}^{n}\left(x_i \tau_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\tau \sum_{i=1}^{n}\left(x_i' \tau_i' / \sum_{i=1}^{n} x_i'\right) \tag{1j}$$

where αi and $\alpha i'$ represent the energy conversion rates in planning and base year, respectively; δi and $\delta i'$ refer to the technical maturity degrees in planning and base year, respectively; τi and $\tau i'$ refer to the service time of energy devices in planning and base year, respectively (a); $\omega\alpha$ is a coefficient for reflecting the energy conversion efficiency; $\omega\delta$ represents the technical factor; $\omega\tau$ is a designed factor representing the service life of the electricity-generation facility. Constraint (1h) required that the energy conversion efficiency of potential energy forms should be better than that in the base year. Constraint (1i) indicated that the provision capabilities of candidate energy forms should be the large than that in the base year. Constraint (1j) ensured that the service time of the facility is as long as possible.

(3) Economic constraints:

$$\sum_{i=1}^{n}\left(x_i \varepsilon_i / \sum_{i=1}^{n} x_i\right) \le \omega_\varepsilon \sum_{i=1}^{n}\left(x_i' \varepsilon_i' / \sum_{i=1}^{n} x_i'\right) \tag{1k}$$

$$\sum_{i=1}^{n}\left(x_i \gamma_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\gamma \sum_{i=1}^{n}\left(x_i' \gamma_i' / \sum_{i=1}^{n} x_i'\right) \tag{1l}$$

where ε_i and ε_i' are the operational costs of two periods, respectively (RMB/kWh); γ_i and γ_i' represent the installed capacity of two periods, respectively (MW); ω_ε is the cost factor involved in the electricity generation; ω_γ is the factor related to installed capacity. Constraint (1k) reflected the requirement in the economic costs of designed energy structure; Constraint (1l) ensured that the economic benefits of optimized energy structure are higher than those of original structure.

(4) Environmental constraints:

$$\sum_{i=1}^{n}\left(x_i \eta_i / \sum_{i=1}^{n} x_i\right) \le \omega_\eta \sum_{i=1}^{n}\left(x_i' \eta_i' / \sum_{i=1}^{n} x_i'\right) \tag{1m}$$

$$\sum_{i=1}^{n}\left(x_i \beta_i / \sum_{i=1}^{n} x_i\right) \le \omega_\beta \sum_{i=1}^{n}\left(x_i' \beta_i' / \sum_{i=1}^{n} x_i'\right) \tag{1n}$$

$$\sum_{i=1}^{n}\left(x_i \lambda_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\lambda \sum_{i=1}^{n}\left(x_i' \lambda_i' / \sum_{i=1}^{n} x_i'\right) \tag{1o}$$

where η_i and η_i' refer to CO_2 amounts discharged from the electricity generation in the years 2010 and 2020, respectively (g/kWh); β_i and β_i' are generated waste amounts in two periods, respectively (g/kWh); λ_i and λ_i' are other environmental impacts of the target and base year, respectively; ω_η, ω_β and ω_λ are the emission coefficients of the carbon, solid waste and other environmental factors, respectively. The constraint (1m) indicated that the new energy structure should have the low CO_2 emissions. The constraint (1n) showed that the optimal energy structure should be associated with the lower waste magnitude. The constraint (1o) indicated that the new energy structure should own a good environmental performance.

(5) Security constraints:

$$\sum_{i=1}^{n}\left(x_i \mu_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\mu \sum_{i=1}^{n}\left(x_i' \mu_i' / \sum_{i=1}^{n} x_i'\right) \tag{1p}$$

$$\sum_{i=1}^{n}\left(x_i \theta_i / \sum_{i=1}^{n} x_i\right) \ge \omega_\theta \sum_{i=1}^{n}\left(x_i' \theta_i' / \sum_{i=1}^{n} x_i'\right) \tag{1q}$$

where μ_i and μ_i' are the reliability factors of the energy exploration in two periods, respectively; θ_i and θ_i' are other security coefficients in two periods, respectively; ω_μ is the control coefficient; ω_θ is the safety factor. The constraints (1p) and (1q) are used to ensure the high efficiency and security of optimal energy structure.

(6) Non-negativity constraints:

$$x_i \ge 0 \tag{1r}$$

To solve the model (1), the weight summation approach is firstly used to tackle three objectives in proposed energy structure optimization model. New objective function (2) is established through allocating three weight coefficients (ω^f, ω^g and ω^h) to original three objectives ($f(x)$, $g(x)$ and $h(x)$), where the compared results among three coefficients reflected the relative importance of corresponding objective functions.

$$Min\ Z = \omega^f \frac{(f_{\max}(x) - f(x))}{(f_{\max}(x) - f_{\min}(x))} + \omega^g \frac{(g(x) - g_{\min}(x))}{(g_{\max}(x) - g_{\min}(x))} + \omega^h \frac{(h_{\max}(x) - h(x))}{(h_{\max}(x) - h_{\min}(x))} \tag{2}$$

where $f_{max}(x)$, $f_{min}(x)$, $g_{max}(x)$, $g_{min}(x)$, $h_{max}(x)$ and $h_{min}(x)$are the possible maximum and minimum values obtained through solving the optimization model with the single objective function of $f(x)$, $g(x)$ and $h(x)$, respectively. Based on above transformation process, original MOSCCP model can be converted to a general single-objective stochastic optimization model. In order to solve this model, the constraints with the random variables should be transformed into their

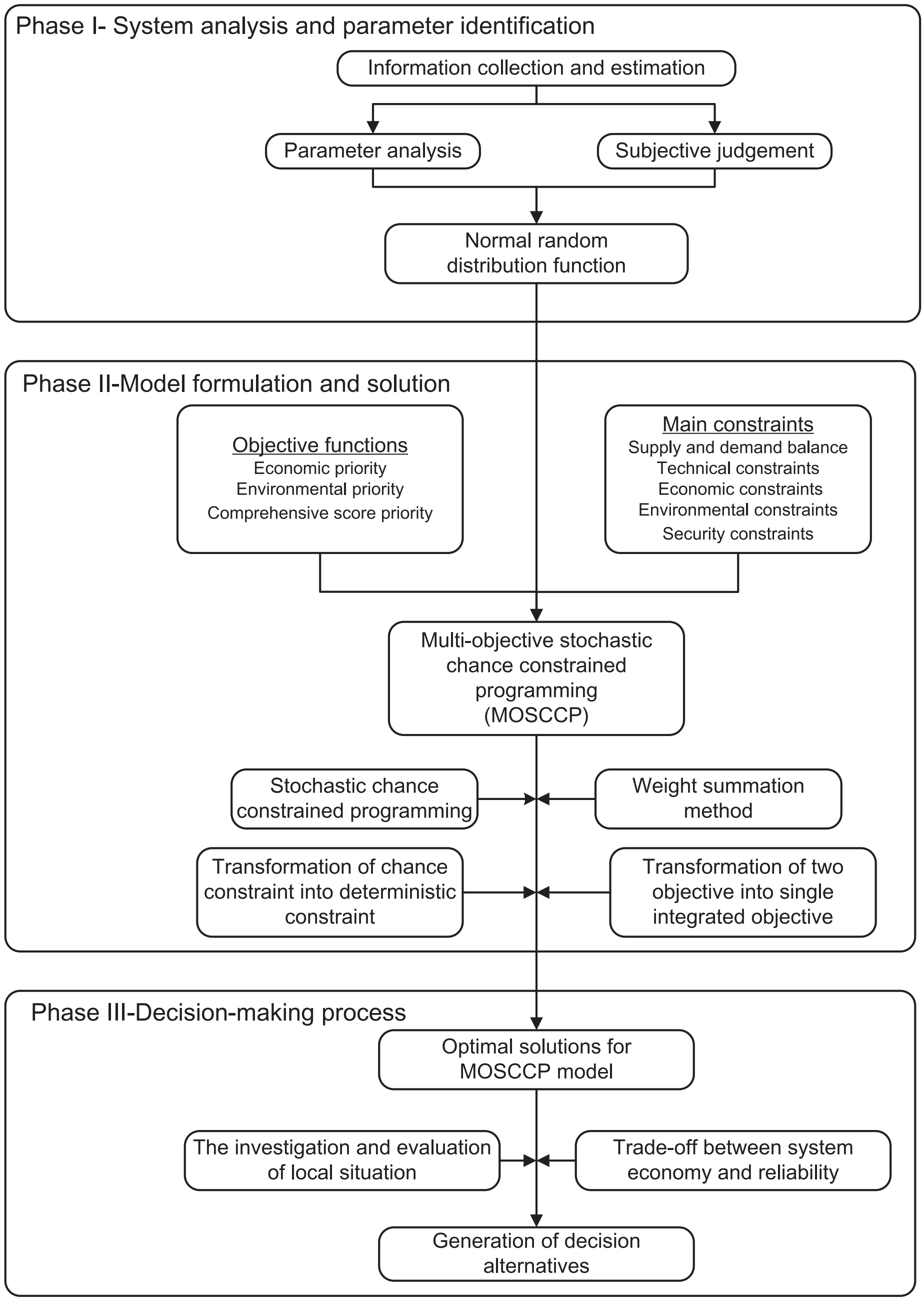

Fig. 1. The formulation and solution framework of MOSCCP model.

deterministic equivalents, which was rewritten as follows (Charnes and Cooper, 1983):

$$P_r\left[\left\{s\left|\sum_{i=1}^{n}x_i \le X_{e\max}(s)\right.\right\}\right] \ge q_z \Leftrightarrow \sum_{i=1}^{n}x_i \le X_{e\max}^{1-q_z}, \quad \forall\ i \tag{3a}$$

$$X_{e\max}^{1-q_z} = F_i^{-1}(X_{e\max}(s)) \quad \forall\ i,\ q_z \tag{3b}$$

$$P_r\left[\left\{s\left|\sum_{i=1}^{n}x_i \ge X_{e\min}(s)\right.\right\}\right] \ge q_z \Leftrightarrow \sum_{i=1}^{n}x_i \ge X_{e\min}^{q_z}, \quad \forall\ i \tag{3c}$$

$$X_{e\min}^{q_z} = F_i^{-1}(X_{e\min}(s)) \quad \forall\ i,\ q_z \tag{3d}$$

where $P_r[\cdot]$ denotes the probability of in the events $[\cdot]$; z is the index of acceptable probability levels of constraints satisfaction, where z = *1, 2, …, Z*, and Z is the total number of given probability level; q_z is the acceptable probability levels; $F_i^{-1}(X_{emax})$ and $F_i^{-1}(X_{emin})$ are the cumulative distribution functions (CDFs) of X_{emax} and X_{emin}, i.e. $[F_i(X_{emax})$ and $F_i(X_{emin})]$. Finally, the deterministic objective function values and decision variables (i.e. f_{opt} and $x_{i,opt}$) at different probability levels (q_z) can be obtained. Fig. 1 shows the framework and procedure for formulating and solving a MOSCCP model, and the detailed steps are described as follows: (i) Data collection, calibration and analysis. (ii) Determine various objective functions for reflecting the system performance comprehensively. (iii) Formulation of the renewable energy structure adjustment optimization model. (iv) To convert the constraints with the random variables to deterministic forms in three acceptable probability levels (i.e. 0.9, 0.95 and 0.99), respectively. (v) Generation of new renewable energy structure schemes under various weight combinations, parameter variations and climate change considerations. According to the preferences of local decision makers, an appropriate solution is considered as the base for the design and

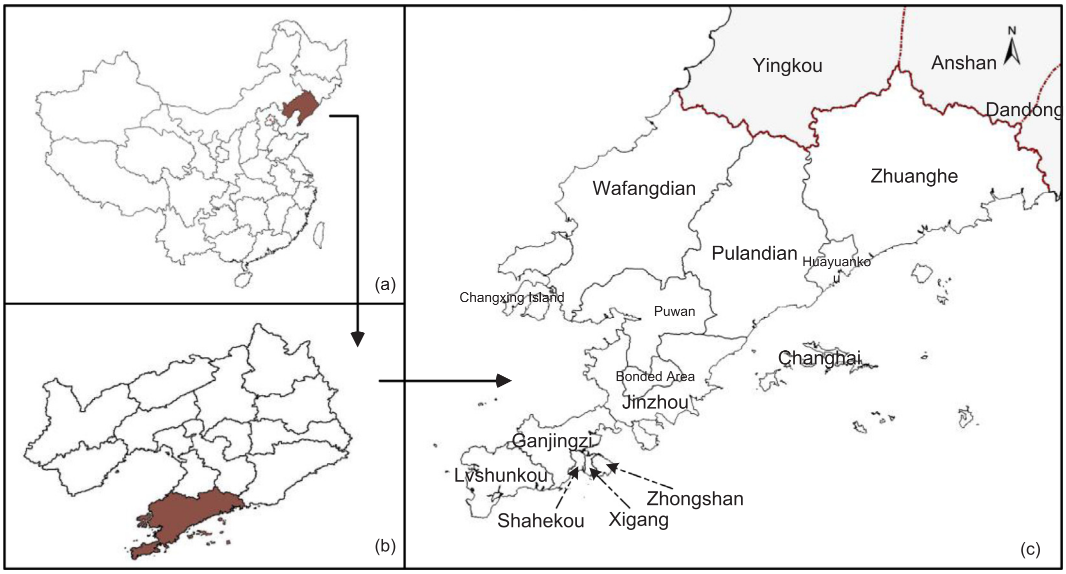

Fig. 2. Sketch map of Dalian: (a) China; (b) Province Liaoning; (c) City Dalian.

execution of final decision scheme.

3. Case study

3.1. Overview of the studied region

As a major coastal city in northeast China, Dalian (38°43′-38°43′N, 120°58′-123°31′E) is situated in the south of the Liaodong peninsula, adjacent to the Bohai Sea and the Yellow Sea, which border on three cities, namely Yingkou, Anshan, Dandong (as shown in Fig. 2). It currently has seven districts (Zhongshan, Xigang, Shahekou, Ganjingzi, Lvshunkou, Jinzhou, and Pulandian), two county-level cities (Wafangdian, Zhuanghe) and one county (Changhai) with a total area of 12,574 square kilometers. By the end of 2017, 5.96 million people were registered in this city, an increase of 20,662 compared with the last year. As the largest port city in Northeast China, Dalian has experienced rapid economic growth. Its GDP in 2016 reached 681.02 billion RMB; among them, the industry realized the added value of 284.99 billion RMB, with an increase of 6.7% over the same period last year, which contribute to 43.6% of the total GDP. It means that the industry has made a great contribution to local economic development, although the large energy consumption and pollutants emission amounts are accompanied with.

Dalian is rich in renewable energy resources, including the wind energy, tidal energy, solar energy, biomass energy and tidal current energy. Belonged to the temperate monsoon region, annual sunshine radiation time of the city Dalian reaches 4000 h, and the theoretical exploited availability of solar energy is 3.68 GW. It has an annual effective wind speed of 6500 h with the annual average wind density of 129.6 w/m^2; meanwhile, the tidal range in this area is 3–4 m and owns the potential of 16.8 million kWh, which is a regular semi-diurnal tide. It is unfortunate that there are few projects related to the renewable energy except limited wind power and nuclear power projects. Currently, new and renewable energy forms only account for less than 5% of total energy consumption. In fact, energy consumption structure of the major cities in China has been dominated by oil and coal for a long time, and then appeared a series of energy crisis and environmental damage problems, which already became a big obstacle to the further development (Zhen et al., 2016). Therefore, how to fully take the advantage of Dalian in the abundant renewable energy development potential and establish a rational, stable and diversified energy structure is a critical issue. The main role of the renewable energy structure optimization model is to improve the original energy structure through increasing the exploited proportion of renewable energy, ensure the renewable energy play a complementary even alternative role to traditional energy, and solve the energy crisis and environmental damage issues finally. The selection of renewable energy type and the determination of optimal exploited amounts are based on in-depth investigation and analysis of the energy demand and supply situations, comprehensive consideration in the utilization costs, operational efficiency and environmental performance of various energy forms.

3.2. The description of the model parameters

Currently, the renewable energy in Dalian mainly includes five forms: wind energy, tidal energy, solar energy, biomass energy and tidal current energy. Moreover, the model selects the years 2010 and 2020 as the base and target year, respectively. The major model parameters are obtained based on the literature review, data collection, field investigation and public and experts consultations of studied region. In detail, available documents mainly included "Diagnosis and life cycle assessment of wind turbine generator", "Calculation and analysis of driving factors of new energy generation efficiency in global 23 countries from 2001 to 2012", "The Strategy on electricity cost reduction in data centers by using energy-storage devices", "Report on the development of wind power industry in Liaoning Province from 2015 to 2019", "Renewable energy, carbon emissions, and economic growth in 24 Asian countries: evidence from panel combination analysis", "New energy generation analysis report in China", and "Outline of the thirteenth five year plan for national economic and social development in Dalian". Moreover, relevant data issued by some departments and authorities also provided well support to the parameter identification, including National Bureau of Statistics of China, Dalian Municipal Bureau of Statistics and National Energy Administration.

As shown in Table 1, model parameters can divide into two types, i.e. fixed values and random variables, respectively. For example, the potential energy availability, energy conversion efficiency, electricity-generation cost, available time, waste production and installed capacity in the base year exhibited stable characteristics, so they are expressed as the fixed values; moreover, other parameters, such as technical maturity, environmental impact factor, exploration reliability index and safety impact factor are also expressed as the fixed values in the base and target years. Table 1 provided their details. Compared with these fixed parameters, the energy demand owns obvious variations due

Table 1
Fixed parameters related to different energy types.

Parameter	Year	Energy type				
		Wind energy	Tidal energy	Solar energy	Biomass energy	Tidal current energy
Net income (RMB/kWh)	2020	0.135	0.08	0.42	0.074	0.15
Available time (h)	2020	6500	1000	4000	6000	1000
Maximum exploration potential at the planning period($\times 10^4$ kWh)	2020	8000	1608	920	1291	1718
Explored volume at the base period ($\times 10^4$ kWh)	2010	450	51	44	11	0
Conversion rate (%)	2010	35	20	17	10	20
	2020	40	25	23	15	25
Electricity-Generation cost (RMB/kWh)	2010	0.546	3	1	0.867	3
	2020	0.494	2.3	0.6	0.737	2.3
Installed capacity (MW)	2010	200	0	0	0	0
	2020	500	2	40	4	2
Discharged CO_2 volumes (g/kWh)	2010	16.5	40.4	75.3	207	40.1
	2020	13.6	38.4	72.1	201	38.6
Discharged solid waste amounts (g/kWh)	2010	1300	1700	1400	2200	1600
	2020	1085	1350	1120	1730	1238
Service lifetime of the power equipment (a)	2010	20	70	25	25	10
	2020	30	80	30	30	15
Security indicator	2010	0.394	0.573	0.331	0.557	0.508
	2020	0.613	0.825	0.851	0.773	0.825
Technical maturity	2010	7	3	7	6	3
	2020	8	4	8	7	4
Environmental impact index[1]	2010	3	4	1	1	2
	2020	4	5	2	2	3
Reliability index	2010	6	4	7	7	4
	2020	7	5	8	8	5

Note: Environmental impact index[1] is used to reflect the influences caused by other pollutants, except for CO_2 and waste.

to the influence caused by the climate change and local socio-economic development. In fact, many components of the energy system may exhibit uncertain characteristics due to the influence of some external factors. According to practical investigated and analytical results of the energy demand, the electricity demand was often affected by some objective factors, such as socio-economic development and temperature change, leading to the large variation. It is thus more suitably expressed as the random normal distribution compared with other two types of uncertain variables, i.e. fuzzy variables or discrete intervals, being $\widetilde{\delta}(s) \sim N(\mu_\delta, \sigma_\delta^2)$. The determination of the characteristics values (i.e. mean value μ_δ and standard deviation σ_δ) is based on predicted electricity demand amounts and designed proportion of renewable energy, where the mean value μ_δ is 8771.97 kWh and standard deviation σ_δ is 31 kWh, respectively.

In this study, the proposed MOSCCP model was solved by the commercial software LINGO 12.0, which is a powerful tool to assist in formulating and solving large-scale and multi-variables optimization models. The previous studies have demonstrated that LINGO is advantageous in tackling the energy and environmental management issues faster and simpler due to its easy-to-edit language and low computational burden (Kong et al., 2010; Wang et al., 2016; Xu et al., 2018). This is the reason why it was used to tackle large-scale energy exploitation and utilization management problems. The hardware setting for running LINGO in this study is listed as follows: (1) Operation System: Microsoft Windows 10; (2) CPU: Intel (R) Core (TM) i7-8550U @ 1.80 GHz 2.00 GHz; (3) RAM: 8 GB. After a few seconds, there were a series of energy exploration and provision patterns under different constraints-satisfactory levels and weighted coefficients, which were useful in evaluating the trade-off between system economy, environmental friendliness and reliability.

4. Result analysis and discussion

4.1. Result analysis

In this study, several tests are accomplished for reflecting the interaction between the weight combinations and acceptable probability levels. Firstly, the value of q_z mainly depends on the attitude of the decision maker to the system reliability and the realization in the system goal. The decision schemes under the high q_z values are helpful in meeting the electricity requirements; meanwhile, the low income and environmental quality are unavoidable. Conversely, the expected realizations in designed three objectives are associated with the low q_z value. Therefore, the range of the q_z value should be wide enough for providing more decision options to local managers. Referring to previous studies (Han et al., 2018; Zhang et al., 2018), three probability levels of constraints satisfaction were designed, i.e. q_z = 0.9, 0.95 and 0.99, respectively. Correspondingly, the designed values of ω^f, ω^g and ω^h are based on the preferences of the decision makers on various system objectives. The assigned high weight coefficient value means that the corresponding model objective was more important than other two objectives, and vice versa. For example, three weight combinations were determined, i.e. economic priority, environmental priority and coordinate development, which are defined as the scenario 1, 2 and 3, respectively. Among them, under the condition of economic priority, the economic coefficient is greater than other coefficients, where $\omega^f = 0.5$, $\omega^g = 0.25$, $\omega^h = 0.25$. The weight coefficient combination under the environmental-friendly scenario emphasized the importance of environmental protection, where the coefficients of environmental factors $\omega^f = 0.25$, $\omega^g = 0.5$, $\omega^h = 0.25$. As for the coordinate development, the same evaluation score is assigned to three objectives, where $\omega^f = 0.33$, $\omega^g = 0.33$, $\omega^h = 0.33$. Table 2 shows the optimal exploration volume and its structural proportion of candidate energy forms provided by MOSCCP model under various conditions. From Table 2, the solutions for reflecting Dalian's energy structure have the large variations under different weights and acceptable probability levels.

Firstly, under stable acceptable level, the variations in the weight coefficient would generate various energy provision alternatives. For example, at an acceptable level of 0.90, under the context of the scenarios 1 and 3, the exploration proportion of wind energy is 83.5% and 87.8%, respectively; the solar energy reaches the maximum exploitable value, being 9.20 million kWh, respectively. The tidal current energy has been improved, compared with 2010, being 5.2% and 0.99%, respectively. Conversely, the explorations of the tidal and biomass energy are maintained at the minimum level in 2010, respectively. This is due to the fact that the economic performances of the tidal energy and biomass energy are poor than other energy forms. Conversely, the wind and solar energy owns low operational cost and high revenue. Moreover, there are many policies and commercial requirements to support the development of the solar industry, indicating that the solar energy still has great exploitation space and potential. As scenario 2 focuses more on environmental protection, the energy exploration pattern under the scenario 2 would become change compared with those of the scenarios 1 and 3. The proportion of the wind energy is the highest, which is up to 92.1%; conversely, the exploration volume of solar energy only comes to 6.15 million kWh, much lower than that in scenario 1 and 3. As for the electric outputs contributed by tidal energy, biomass energy and tidal current energy, they are remained at a low level, being 0.51, 0.11 and 0 million kWh, respectively. The reason mainly lies in the fact is that the CO_2 emission and waste generation exert more influences on the provision patterns. The CO_2 emission (13.6 g/kWh) and solid waste generation (1085 g/kWh) of the wind energy are the smallest; meanwhile, above two indicators of the solar energy also are advantageous than those of other three energy forms, leading to obvious differences in the provision amounts among various energy forms. These phenomena appeared in an acceptable level of 0.90 also appeared under other two levels of 0.95 and 0.99, such that it is not

Table 2
Part of solutions from MOSCCP model under various conditions.

Weight combination	Acceptable probability level	Objective value			Total amount ($\times 10^4$ kWh)	Exploration volume ($\times 10^4$ kWh)				
		f(x)[1]	g(x)[1]	h(x)[1]		Wind energy	Tidal energy	Solar energy	Biomass energy	Tidal current energy
Group 1[2]	0.90	1444.40	1578.29	1.34	8732.24	7295.69	51.00	920.00	11.00	454.55
	0.95	1442.86	1576.57	1.34	8720.98	7285.15	51.00	920.00	11.00	453.83
	0.99	1439.99	1573.36	1.33	8699.85	7265.38	51.00	920.00	11.00	452.47
Group 2[2]	0.90	1326.00	155587.60	0.74	8550.19	7873.16	51.00	615.02	11.00	0.00
	0.95	1328.05	155833.56	0.74	8561.45	7882.84	51.00	616.61	11.00	0.00
	0.99	1331.75	156294.90	0.74	8582.58	7900.99	51.00	619.58	11.00	0.00
Group 3[2]	0.90	1438.87	178055.40	1.10	8732.24	7664.21	51.00	920.00	11.00	86.03
	0.95	1437.34	177897.70	1.10	8720.98	7653.13	51.00	920.00	11.00	85.85
	0.99	1434.49	177602.00	1.10	8699.85	7632.34	51.00	920.00	11.00	85.51

Note: f(x)[1] represents the total system revenues, (10^4 RMB); *g(x)*[1] is the carbon emission volumes during the energy exploitation and utilization processes, (ton); *h(x)*[1] is used to reflect the exploration ratio of various energy forms.
Group1[2], 2[2] and 3[2] represent three weight combinations, i.e. economic priority, environmental priority and coordinate development, respectively.

discussed repeatedly here.

In addition, when weight coefficient remains unchanged, the variations in designed probability level q_z also cause various energy structure forms. For instance, under the scenario 1, when q_z is increased from 0.90 to 0.99, the exploited amounts of the wind energy were reduced slightly, being 72.96, 72.85 and 72.65 million kWh, respectively. Similarly, the power generation of tidal current energy also becomes decrease, being 4.55, 4.54 and 4.52 million kWh, respectively. As for the supplied amounts of other three energy forms (i.e. tidal, biomass and solar energy), they remain unchanged, where the solar energy reaches its maximum availability, being 9.2 million kWh; while the outputs of the tidal energy and biomass energy are the minimum, being 0.51 and 0.11 million kWh, respectively. This is because the increase in q_z would lead to the decrease in regulated maximum values of energy demand, which might explain why the wind and tidal current energy provisions with the unit income ranking in the middle position were decreased. Variational energy structure form appears in the scenario 2. The exploited amounts of the wind energy and solar energy were raised slightly with the increase of q_z, where the exploration volumes of the wind energy reach 78.73, 78.83 and 79.01 million kWh, respectively; those of the solar energy are 6.15, 6.17 and 6.20 million kWh, respectively. The electricity outputs attributed to other three energy forms remain unchanged, reaching its minimum availability, respectively. This is due to the fact that in the scenario 2, the electricity provision amounts should be as small as possible in order to satisfy the environmental quality requirements. Therefore, the increased minimum electricity demand leads to the increase in some candidate energy forms. Actually, the weight design and the selection of constraint-satisfaction level not only affect the decision variables, but also the objective function. As demonstrated in Fig. 3, the total system income and CO_2 emissions under two scenarios 1 and 3 would decrease as the increase of the constraint-satisfaction level; conversely, they become increase at scenario 2. This is due to the fact that the objective values are positively correlated with the energy exploration volume, their variation trends should remain consistent. As indicated in above comparison and analysis results, the wind energy owns the largest exploration amounts under various conditions, the second is solar energy, the third is tidal current energy, then is tidal energy, and the last one is biomass energy. The exploration pattern under the scenario 1 at an acceptable level of 0.9 is recommend as the design basis of the energy structure adjustment in the future, since it could ensure the dominant role of the wind energy, encourage the utilization of the solar energy and tidal current energy, and emphasize balanced development of multiple energy forms.

4.2. Discussion

Previous studies have shown that extreme weather can pose a threat to energy production, supply and transport, in particular, it is more obvious that when renewable energy as the main form of energy system (Ruth and Lin, 2006). Renewable energy, as an important energy form, is growing rapidly in recent years due to it aims to reduce the carbon emissions and mitigate the climate change (Schmidt et al., 2016). However, the exploration and utilization of renewable energy mainly depends on the magnitude and stability of meteorological elements such as precipitation, wind speed, solar radiation, temperature and humidity. The dramatic variations in meteorological factors (i.e. wind velocity, the amount of sunshine and rainfall) caused by climate change may affect the power generations of wind, photovoltaic and hydroelectricity, further exacerbate the complexity of power system planning and management. It will also bring more adverse influences on the power supply and demand balance and energy security. With the rapid urbanization of Dalian, the extra pressure caused by climate change exerted on the energy planning and management system to be significant. Therefore, how to examine the influences caused by the climate change on energy demand and availability amounts and incorporate these evaluation results into the energy structure adjustment optimization model become the necessary and crucial.

4.2.1. Impact analysis of climate change on the energy demand and supply

4.2.1.1. Impact of climate change on the energy demand. It is well known that the climatic change and its variation extent exert the influence on the energy demand (Owusu and Asumadusarkodie, 2016). For example, the relevant reports from the National Energy Agency indicated that severe weather events, such as cold and high temperature, have a serious impact on local daily heating and cooling demand. Therefore, the potential effect exerted by the temperature change on local energy requirements was examined. Under the context of urban heat island effect, annual average temperature of Dalian has increased markedly. It is estimated that the minimum and maximum value of the renewable energy demand in 2020 will increase by 1%, 3% and 5% under three scenarios *a*, *b* and *c*, respectively. The minimum values will reach 85.96, 87.66 and 89.36 million kWh, respectively; the maximum values will reach 88.60, 90.35 and 92.11 million kWh, respectively.

4.2.1.2. Impact of climate change on the wind power provision. The major feature of the wind energy is its instability and intermittence subjected to the wind speed and direction. The investigated results demonstrated that the average wind velocity of Dalian in the past 60 years is 4.8 m/s with a decline rate of 0.24 m/s every ten years. The output of wind energy in the future is estimated based on the following equation (Wu

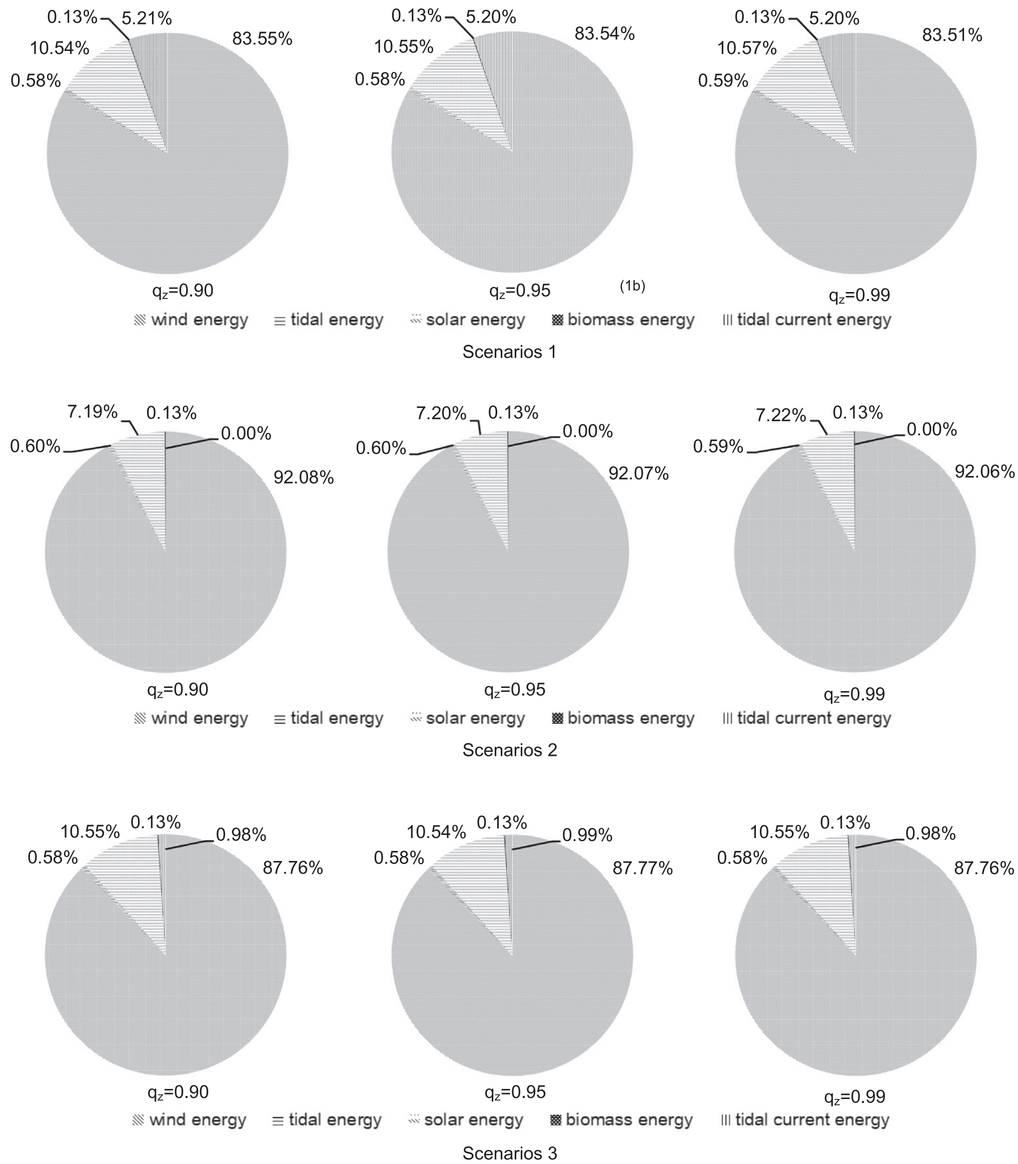

Fig. 3. The proportion of various renewable energy forms.

et al., 2016):

$$P_{wt} = \begin{cases} 0, & 0 \leq V_t \leq V_{ci},\ V_t \geq V_{co}, \\ P_{wR} \times (V_t^3 - V_{ci}^3)/(V_R^3 - V_{ci}^3), & V_{ci} \leq V_t \leq V_R \\ P_{wR}\ V_R \leq V_t \leq V_{co} & \end{cases} \tag{4}$$

where P_{wt} is defined as the output power of wind turbine generator (kW), while V_t is the wind speed at t moment, (m/s); P_{wR} is the nominal power of wind turbine generator, (kW); V_{ci}, V_{co} and V_R represent the cut-in wind speed, cut-out wind speed and rated wind speed, respectively, (m/s). Eq. (4) can be used to calculate the maximum provisions of the wind energy under three various scenarios in 2020. The variation coefficients of power output are 0.98, 0.96 and 0.94 respectively; correspondingly, the maximum power generations reach 78.43, 76.89 and 75.38 million kWh, respectively.

4.2.1.3. Impact of climate change on the solar power provision. Based on solar radiation data provided by the National Meteorological Information Center of China Meteorological Administration, it is concluded that Dalian is rich in solar energy resources, and its annual average value of total solar radiation reaches 4999 MJ/m^2. According to the statistics, total radiation level in Dalian will decrease at the average rate of 11.6 (MJ/m^2)/a. At present, there are many computational methods to estimate annual average power generation of photovoltaic power station, including the standard method, module area method, and hourly solar radiation method. The solar radiation available on the tilted surface is used to calculate the hourly energy output as follows (Amutha and Rajini, 2016):

$$E_P = A \times H \times P \times K_S \tag{5}$$

where A indicates the total solar panel area, (m2); H is supposed as the annual average solar radiation on the tilted panels, (MJ/m^2·a); P is solar panel yield, (%); K_S is the performance ratio. The parameter H is influenced by the climate change. Based on Eq. (5), the maximum photovoltaic power outputs under the climate change are reduced to 9.02, 8.84 and 8.87 million kWh, respectively.

4.2.1.4. Impact of climate change on the tidal and tidal current energy provision. In the past 50 years, the rainfall in Dalian shows a decline trend under the global warming, which is basically consistent with the precipitation change in Northeast China. The average annual precipitation in Dalian in the past 60 years is 617.6 mm with a decrease rate of 18.60 mm per 10 years, which directly leads to the

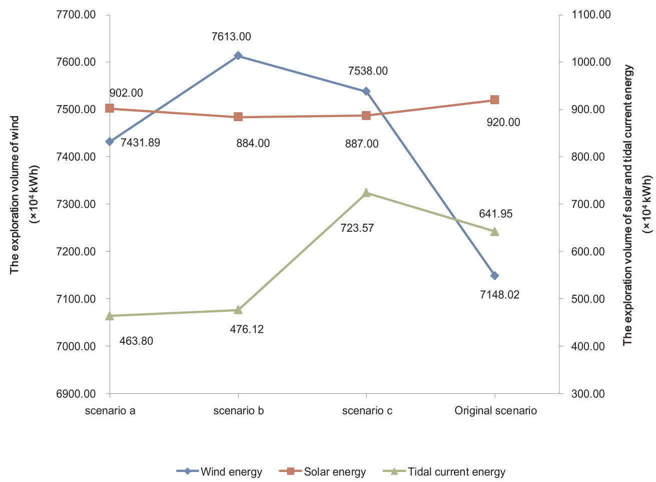

Fig. 4. The variation tendency of renewable energy exploitation in the context of climate change.

decrease in tidal energy and tidal current energy outputs. The energy provisions of hydropower facilities mainly depend on the runoff, head loss and the energy loss caused by the electromechanical equipment, where the power outputs of the tidal and tidal current energy are estimated approximately based on the following equation (Amutha and Rajini, 2016):

$$P_{ht} = F_t \times H_w \times G \quad (6)$$

where F_t is the water flow rate, (l/s); H_w represents the net hydro-head, (m); G is gravitational acceleration, (m^3/s). It is predicted that the maximum power generation capacity of tidal power in 2020 reaches 16.08 million kWh, while tidal current power is 17.18 million kWh. Under the context of the climate change, the maximum electric outputs of tidal energy generation are estimated at 15.28, 14.47 and 13.67 million kWh respectively; correspondingly, the outputs of tidal current energy are 16.32, 15.46 and 14.60 million kWh, respectively.

4.2.2. Results analysis under climate change

Fig. 4 shows the optimal exploited amounts of various renewable energy forms in the planning year under climate change. Compared with Table 2, it can be found that exploited quantity and percentage of candidate energy sources own obvious variations. Firstly, the influences caused by climate change on the biomass energy are ignored, where the biomass energy is always unpopular. Secondly, the tidal energy has the lowest installed capacity; meanwhile, its economic and environmental performances are only better than those of biomass energy, so it is unpopular either. Thirdly, the outputs of wind energy were increased and accounted above 80 percent of total provision amounts, being 78.43, 76.89 and 75.38 million kWh, respectively. This is due to the fact that wind energy owns the advantages in the technical, economic and environmental aspects. Its exploited volume would increase, although its maximum availability is slightly reduced due to the climate change. Fourthly, the utilization of solar energy has declined slightly, but the exploited quantity reaches its possible maximum value. This is because the total energy demand is increased under the climate change, it is required that some energy forms having obvious advantages (i.e. wind and solar) play more important role. Finally, as a new energy source, exploited amount of the tidal current energy remains unchanged under two scenarios *a* and *b*, but increases remarkably under the scenario *c*. The reason is that the wind and solar energy has reached the maximum exploitable amount in the scenario *c*; meanwhile, the tidal energy and biomass energy has been maintained at the basic level, such that the tidal current energy is mainly used to meet increased energy demand.

Through the above comparison and analysis, it is concluded that designed three scenarios under climate change effectively considered potential imbalance problems of energy supply and demand, where the influences exerted by main meteorological factors (i.e. temperature, wind speed, rainfall and solar radiation) on energy demand and supply are incorporated into the parameters estimations of the optimization model. This would lead to a fact that generated energy provision alternatives under climate change are capable of alleviating even eliminating the risk of electricity shortage and improving the stability and reliability of the energy structure patterns. The obtained results are beneficial to decision makers to understand local energy situation and design the energy structure adjustment scheme in the future. However, formulated energy structure adjustment optimization model still has many aspects need to be improved. For example, the weight summation approach is used to solve this multi-objective optimization model. In fact, many types of multi-objective methods are developed, including the ε-constraint method and the minimax approach. How to select an appropriate solution method through the comparison analysis is very critical. Moreover, the impact evaluation of the climate change on energy supply and demand is simple and rough, and it is just a trend prediction. The high resolution prediction results based on the Regional Climate Models (RCMs) should be incorporated into the power generation calculation processes in order to obtain adaptive energy exploration patterns to the climate change. Finally, two other types of the uncertain optimization techniques, i.e. FMP and ILP model, should be incorporated into model to handle more-complex management problems.

5. Conclusion

In this study, a multi-objective stochastic chance constrained programming model was developed. The model results provided by formulated MOSCCP model emphasized the dominant position of wind and solar energy in entire renewable energy system and complementary role of the tidal energy, which is completely consistent to current situation of the Dalian city and demonstrated its practicability and rationality. Moreover, the variations in the weight coefficients, constraints-satisfactory levels and climate change scenarios exert the influences on obtained results, which effectively reflected the importance of managers' subjected preferences on economic development, environmental protection and adaption to climate change. Furthermore, the impact evaluation of climate change on the energy supply and demand is incorporated into the optimization model, which is beneficial to generate the adaptive energy exploration patterns to the climate change. Since it realized the coordinate development of socio-economy and environment through improving the exploration ratios of wind and solar energy dramatically, the exploration pattern under the scenario 1 at an acceptable level of 0.9 is recommended as the design basis of the energy structure adjustment in the future. In order to further enhance the practicability and reliability of MOSCCP model, the studies about how to select an appropriate multi-objective solution method and incorporate high resolution prediction results into the optimization model are critical; at the same time, two other types of uncertain optimization techniques, i.e. FMP and ILP model, have potentials to be incorporated into model to handle more-complex management problems.

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